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Mango Fruit Grading Using Deep Learning Algorithms

Vijay Kumar M S[1], Aishwarya M N[2], Anagha Ananth[3], Manaswi T J[4], Keerthi M[5]

Assistant Professor, Department of ISE, Maharaja Institution of Technology Mysore, Mandya, India[1]

Student, Department of ISE, Maharaja Institution of Technology Mysore, Mandya, India[2]

Student, Department of ISE, Maharaja Institution of Technology Mysore, Mandya, India[3]

Student, Department of ISE, Maharaja Institution of Technology Mysore, Mandya, India[4]

Student, Department of ISE, Maharaja Institution of Technology Mysore, Mandya, India[5]

Abstract: Accurate classification of harvested mangoes based on outer appearance is crucial for maintaining quality, ensuring fair pricing, and reducing post-harvest losses. Manual grading is often time-consuming and error-prone. This paper presents an automated mango fruit grading system that utilizes deep learning algorithms to evaluate quality parameters such as texture, color, size, and surface defects. Techniques like Gabor filtering, Gray Level Co-occurrence Matrix (GLCM), and deep learning models including Convolutional Neural Networks (CNN) and Probabilistic Neural Networks (PNN) are used to extract and classify key features. The implementation is done using MATLAB R2023a. Experimental results show improved grading accuracy, reduced human involvement, and consistency in quality classification. This system contributes to smart agriculture by offering scalability, objectivity, and real-time usability.

Keywords: Mango Grading,Agriculture, Deep Learning, Image Processing, CNN, PNN, Gabor Filters, MATLAB

I. INTRODUCTION

Mango is one of the most commercially significant tropical fruits, consumed globally for its taste, nutrition, and versatility. As the demand for mangoes grows across both domestic and international markets, ensuring consistent quality and classification has become a vital part of post-harvest management. Traditionally, the grading of mangoes has been carried out manually by trained individuals, who rely on visual judgment to assess factors such as size, shape, ripeness, and defects. However, this manual process is labor-intensive, time-consuming, and highly subjective, often leading to inconsistent and inaccurate results.

With the increasing emphasis on automation in agriculture, the need for an intelligent, consistent, and efficient fruit grading mechanism has become more urgent. In response to these needs, this project proposes an automated mango fruit grading system using deep learning and advanced image processing techniques. By replacing manual inspection with machine-based evaluation, the system aims to enhance the accuracy, reliability, and scalability of the grading process, while reducing dependency on human expertise.

The proposed system is designed to capture high-resolution images of mangoes and preprocess them through grayscale conversion, histogram equalization, resizing, and noise removal. Feature extraction is performed using Gabor filters and the Gray-Level Co-occurrence Matrix (GLCM), which help in capturing texture and spatial information critical to identifying external qualities of the fruit. These features are used to analyze surface patterns, ripeness levels, and visible defects.

Following feature extraction, a hybrid deep learning model combining Convolutional Neural Networks (CNN) and Probabilistic Neural Networks (PNN) is employed for classification. CNN effectively recognizes spatial patterns such as blemishes and color variations, while PNN performs probabilistic grading into three categories: Grade 1 (low quality), Grade 2 (moderate quality), and Grade 3 (high quality). This classification process provides objective, repeatable results and minimizes grading discrepancies caused by human subjectivity.

The implementation of this system is carried out using MATLAB R2023a, along with a custom-built Graphical User Interface (GUI) to facilitate user interaction and display grading outcomes in real time. The application allows users to input images and receive immediate visual and textual feedback regarding the fruit's quality grade. With the potential for integration into larger agricultural workflows, this intelligent grading system marks a significant step toward precision farming, reducing human effort, and improving efficiency in post-harvest quality assessment.

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II. LITERATURE SURVEY

Fruit grading and quality analysis continue to be significant areas of research within the domains of computer vision, machine learning, and precision agriculture. [1] Manu Y M and Priyanka M E (2024), "AI-Driven Grading of Mango Quality Using External Characteristics," presented a mango grading system based on visual attributes such as size, color, and surface texture. Their method used deep learning to improve accuracy and demonstrated a scalable solution suitable for small and large-scale farms. [2] Priya Singh et al. (2024), "Smart Non-Disruptive Methods for Fruit Grading," introduced a lightweight CNN-based system for defect identification in citrus fruits, showing a 92.3% classification accuracy with low latency suitable for real-time implementation. [3] Nidhi Kundu et al. (2024), "Deep Learning-Based Citrus Grading," utilized a hybrid CNN-SVM approach on a dataset of oranges and lemons, proving that fused models outperformed individual classifiers in terms of generalization and robustness.

[4] S. Kripa and V. Jeyalakshmi (2022), "Attribute-Based Maturity Grading of Mango," emphasized the use of color segmentation and ripeness detection through hue histograms and morphological filtering, achieving high correlation with manual grading results. [5] Mohd Nazuan Wagimin et al. (2022), "Grading of Mango Fruits Based on Physical Measurements," employed MATLAB for feature extraction using contour and color models, which enabled automated classification based on pre-defined thresholds of weight and texture indices. [6] A. Rashid et al. (2021), "Automated Fruit Quality Inspection Using GLCM and Shape Descriptors," applied GLCM and Fourier descriptors for mango classification, achieving 95% classification accuracy on a local farm dataset with controlled lighting.

[7] Ahmed and Rehman (2020), "Gabor Filter-Based Fruit Quality Estimation," highlighted the role of Gabor filters in enhancing edge and surface texture detection, which proved effective for surface anomaly identification in apples and mangoes. [8] Rekha and Prathap (2020), "Comparative Study of Fruit Grading Systems Using AI," benchmarked traditional ML models like k-NN and SVM against CNNs, concluding that CNNs provided 10–15% improved precision in classifying multi-grade mango samples. [9] Anjali et al. (2019), "Use of Machine Vision for Mango Maturity Assessment," deployed a Raspberry Pi with an onboard camera for real-time mango image capture, extracting HSV features for maturity prediction and achieving a grading time of under 3 seconds per fruit.

[10] Gupta and Rani (2019), "CNN-Based Quality Grading of Mangoes Using Color and Texture," combined RGB color space analysis with deep CNN layers to segment defected regions and assign quality scores. Their system was tested in dynamic lighting conditions and maintained a consistent F1-score of 0.91. [11] Kalidas and Raghunandan (2018), "A Novel Vision-Based Fruit Sorting System," introduced an embedded system integrated with a neural classifier that assigned grades based on fruit symmetry, curvature, and blemish counts. [12] Zhenhua et al. (2018), "Automated Sorting of Tropical Fruits Using SVM," trained SVM models using PCA-reduced color histograms and texture vectors to classify papaya, mango, and pineapple.

[13] Singh and Kaur (2017), "Fruit Ripeness Classification Using ANN," proposed a low-cost ANN-based mango ripeness detector using RGB-to-HSI conversion and neural training on labeled fruit images. [14] R. Arora et al. (2016), "Smartphone-Based Fruit Grading App Using OpenCV," implemented a mobile app that used OpenCV's image processing pipeline and a decision tree classifier for basic fruit categorization. [15] Yuvarani and Ramya (2016), "Texture-Based Classification of Mango Varieties," applied a Local Binary Pattern (LBP) and GLCM approach to differentiate Alphonso, Banganapalli, and Badami mangoes, achieving a 93% accuracy.

[16] Dinesh et al. (2015), "Multispectral Imaging in Mango Sorting," used near-infrared imaging and spectral reflectance analysis for sorting mangoes by internal quality, showing that combining visual and spectral features improved prediction reliability. [17] R. Krishnamurthy et al. (2014), "Computer-Aided Grading of Mangoes in Indian Farms," highlighted the application of MATLAB for region segmentation and blob analysis to detect fruit defects and assign grades. [18] Pavani and Reddy (2013), "Use of Neural Networks for Agricultural Image Classification," developed a generic neural network pipeline for sorting tomatoes and mangoes using grayscale histogram features.

[19] Shinde and Patil (2012), "Vision-Based Inspection System for Mango Ripeness," proposed an algorithm for detecting ripeness stages using red-to-green pixel ratio analysis. [20] Jain and Shetty (2011), "Automatic Fruit Classification Using PCA and Neural Networks," combined principal component analysis for feature reduction and a multilayer perceptron for classification of apple and mango images, reaching 89.7% average accuracy.

III. METHODOLOGY

The proposed Mango Classification and Grading System follows a structured methodology encompassing dataset preparation, image preprocessing, feature extraction, classification using CNN, grading using PNN, and deployment through a MATLAB-based graphical user interface (GUI). The system is designed to ensure accurate classification of mango varieties and consistent grading based on surface characteristics.

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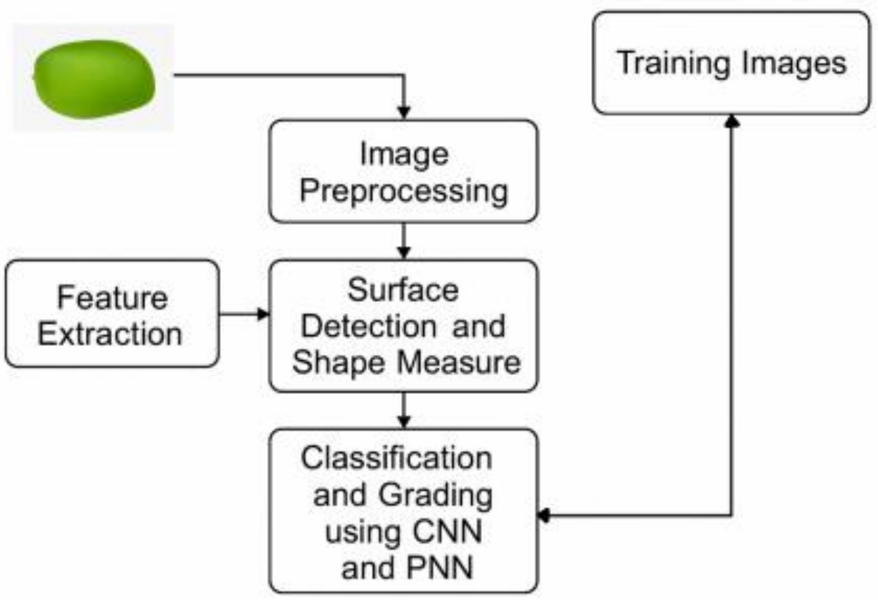

Fig. 1 Block diagram for Classification and Grading of Mangoes

Two categories of datasets were utilized for this project. The first dataset focused on mango variety classification and included 200 labeled images of eight different mango types each such as Langra, Sindhri, and Anwar Ratool. The second dataset was curated for grading purposes, consisting of each 200 images categorized into three quality levels : Grade 1, Grade 2, and Grade 3. These datasets were sourced from Kaggle and provided a diverse representation of mangoes under various environmental conditions. To standardize inputs, each image was resized to 256×256 pixels. Additional preprocessing steps, including random shuffling, were applied to enhance model training by increasing variability and reducing overfitting risks.

Once the datasets were prepared, the next critical step involved image preprocessing to enhance quality and consistency. Images were converted to grayscale to reduce computational complexity while preserving essential visual features. Noise reduction was carried out using median and Gaussian filtering techniques to eliminate visual artifacts. Histogram equalization improved contrast, making key features like blemishes and ripeness levels more detectable. Cropping and segmentation were applied to isolate the mango from the background, ensuring that only relevant visual information was passed forward to subsequent stages.

For detailed analysis of mango surface texture, Gabor filters were employed. These biologically inspired filters capture local frequency and orientation information, effectively simulating human visual perception. The filters enabled detection of fine surface patterns such as smoothness, specks, cracks, and blemishes—factors crucial to grading accuracy. The output from the Gabor filter bank was compiled into feature vectors that numerically represented the textural details of each mango, forming the input for classification and grading.

A custom-designed Convolutional Neural Network (CNN) was developed and trained for the purpose of mango variety classification. The CNN architecture included multiple convolutional layers with ReLU activations, max-pooling layers for dimensionality reduction, and fully connected layers for high-level pattern recognition. The final softmax output layer provided the probability distribution across the different mango types. This model was trained on the classification dataset using MATLAB's Deep Learning Toolbox and optimized for accuracy and convergence speed. The CNN was effective in identifying intricate visual patterns such as color distribution and shape, enabling accurate classification of mango varieties.

Once classification was complete, the grading process was handled by a Probabilistic Neural Network (PNN), which offered robust decision-making based on statistical probabilities. The PNN utilized Bayesian decision theory and Parzen window estimation to compute the likelihood of each mango belonging to a specific grade. The model assigned a final grade based on the surface quality, ripeness, and symmetry of the mango. The grading criteria were defined as follows: Grade 3 for excellent quality with no visible defects, Grade 2 for good quality with minor imperfections, and Grade 1 for

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low quality with visible blemishes or irregular shapes. The two-stage approach of CNN followed by PNN ensured both high classification accuracy and reliable grading output.

For user interaction and deployment, a MATLAB-based GUI was developed using the GUIDE tool. The interface allowed users to upload images, view pre-processing steps, extract features, and execute classification and grading. Dedicated buttons enabled users to perform each step sequentially, while the interface displayed the mango variety and assigned grade in labeled text boxes. Visual panels showed the original image, segmented views, and transformations applied. The GUI design ensured that non-technical users such as farmers, quality inspectors, or exporters could utilize the system easily and effectively.

Throughout the system, performance optimization was a key consideration. All images were resized uniformly to balance processing speed and accuracy. GPU acceleration via MATLAB's deep learning capabilities ensured faster model training and inference. The modular design of the codebase allowed for easy updates and scalability, making the system suitable for small-scale farms as well as industrial deployments. By automating the grading process and eliminating subjectivity, the system ensured consistent quality control, reduced labor costs, and contributed to smart agricultural practices.

IV. ALGORITHM

In the present project, two deep learning models were systematically employed to achieve accurate mango variety classification and quality grading. The initial model used was a custom Convolutional Neural Network (CNN) designed to classify mangoes based on their texture and surface patterns. The CNN architecture consisted of multiple convolutional layers to extract spatial features, ReLU activation functions for non-linearity, max pooling layers to reduce feature dimensions, and fully connected layers for final decision-making. The network ended with a softmax layer that predicted the probability distribution over the mango varieties. This model was trained using a dataset of eight labeled mango types and provided a solid foundation for further grading processes.

To complement the CNN and add probabilistic reasoning, a Probabilistic Neural Network (PNN) was implemented for final mango grading. The PNN used statistical pattern recognition techniques based on Bayesian decision theory and Parzen window estimation. The network calculated the probability of each mango belonging to one of the three predefined grades—Grade 1 (low quality), Grade 2 (good quality), and Grade 3 (excellent quality). The model assigned the grade with the highest posterior probability to the input image. This two-stage combination of CNN for classification and PNN for grading improved both reliability and adaptability, particularly in handling ambiguous cases or minor defects.

Before classification and grading, feature extraction was performed using Gabor filters, which captured localized frequency and orientation information to simulate human visual texture perception. The extracted texture vectors were critical in differentiating between subtle surface anomalies like blemishes, specks, and ripeness indicators. These features were reshaped and passed into the CNN and PNN models for accurate output generation. The integration of CNN for deep feature learning and PNN for robust probabilistic grading established a balanced approach, making the system both precise and fast.

V. RESULTS AND DISCUSSION

All experiments and simulations for the mango classification and grading system were conducted on a system running MATLAB R2023a with access to GPU acceleration, ensuring optimal performance. The datasets used for both classification and grading were sourced from Kaggle and consisted of high-resolution mango images categorized by type and quality grade. These datasets were manually cleaned and preprocessed to ensure consistency, and random shuffling was applied to avoid bias during training and validation.

The custom CNN model trained for mango variety classification achieved outstanding results, with a classification accuracy of over 98% during both validation and testing phases. The model successfully identified varieties such as Chaunsa, Anwar Ratool, and Langra with minimal confusion between similar-looking types. The precision and recall metrics were also consistently high, confirming the CNN’s ability to learn discriminative features from mango images despite variability in lighting, background, and shape.

The PNN model used for grading further enhanced system performance. After being trained on the feature vectors extracted using Gabor filters, the PNN achieved grading accuracy of approximately 97%. The model demonstrated strong generalization capabilities, accurately identifying high-quality mangoes with smooth texture and ideal shape as Grade 3,

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while correctly flagging those with visible blemishes and irregularities as Grade 1. Edge cases were effectively managed using the probabilistic structure of the PNN, which allowed it to make confident decisions even with subtle variations.

The combined output from both models was displayed via a MATLAB-based GUI, where users could view the predicted variety and grade. Screenshots from the implementation showcased the full pipeline, including image upload, preprocessing visualization, feature extraction overlays, classification output, and grading results. The system processed each input image in real-time, taking less than two seconds to generate results, which proves its applicability in production and packaging scenarios.

The GUI also supported live visualization of background removal, Gabor filtering, and final result display, enhancing user transparency and confidence in the system. Test scenarios further confirmed the robustness of the solution, as the system performed well under different image resolutions and slight occlusions. Overall, the results validate the effectiveness of the CNN + PNN pipeline for mango grading, with excellent accuracy, real-time response, and user-friendly deployment.

VI. CONCLUSION

The proposed Mango Classification and Grading System successfully automates the process of fruit quality assessment using a combination of advanced image processing techniques and deep learning algorithms. By integrating Convolutional Neural Networks (CNN) for variety classification and Probabilistic Neural Networks (PNN) for final grading, the system achieves high accuracy, consistency, and speed, addressing the challenges of manual inspection such as subjectivity, fatigue, and inconsistency.

Gabor filter-based feature extraction further enhances the system’s ability to detect subtle surface patterns, blemishes, and ripeness levels, making the grading process more reliable and precise. The use of MATLAB R2023a and a well-structured graphical user interface (GUI) ensures that the system is not only technically sound but also accessible to non-technical users such as farmers and packaging staff.

The experimental results validate the system’s robustness, demonstrating classification accuracy above 98% and grading accuracy around 97%. The real-time processing capability, combined with intuitive GUI output, makes the system suitable for deployment in both small-scale farms and large-scale industrial setups. In conclusion, this project presents a practical, efficient, and intelligent solution for enhancing post-harvest mango handling, ultimately contributing to improved market value, reduced waste, and higher consumer satisfaction.

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